Chapter 7
Assortativity and Hierarchy in Localized R&D Collaboration Networks

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Abstract One of the challenges of innovative clusters relies on their ability to overlap technological domains in order to maintain their growth path along the cycle of technological markets. The paper studies two particular structural properties of collaboration networks that provide new insights for understanding this overlapping process. On the one hand, the degree distribution of knowledge networks captures the level of hierarchy within networks. It gives a first measure of the ability of networked organisations to coordinate their actions. On the other hand, the degree correlation captures the level of assortativity of networks. It gives a measure of the ability of knowledge to flow between highly and poorly connected organisations. We propose to combine these simple statistical measures of network structuring in order to study the parameters window that allow localized knowledge networks combining technological lock-in with regional lock-out.

7.1 Introduction

The study of R&D collaboration networks has become a subject of a growing interest in spatial analysis and geography of innovation (Autant-Bernard et al. 2007; Scherngell and Barber 2011). In particular, clusters analysis have found through the identification of localized R&D collaboration networks new means for assessing regional performances (Owen-Smith and Powell 2004; Vicente et al. 2011;

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Balland et al. 2013), beyond the simple co-location of innovative activities or the black box of local knowledge spillovers (Breschi and Lissoni 2001).

Our contribution fits with this research challenge, with a particular focus on the ability of localized R&D collaboration networks to maintain a long term performance in a context of rapid business and technological cycles. The aim is to capture the structural properties of collaboration networks that allow clusters performing in particular technologies without compromising their renewal capabilities when markets for these technologies decline. As a matter of fact, some clusters can have difficulties in coping with technological and market decline, even if they were leading places during the maturity stage of the industry. At the opposite some others can succeed in disconnecting their cycle to the cycle of technologies by reorganizing resources and networks towards a new stage of growth based on a new or related growing market. Literature provides some highlighting stylized facts of such patterns of cluster evolution. For instance, Saxenian (1990) describes the renewal of the Silicon Valley in the 1980s from the declining semiconductor industry towards the emerging computer industry. She stresses on the fact that such a renewal was more the consequence of a reorganisation of knowledge flows into the local organisational network rather than the consequence of market or national policy concerns. Tödling and Trippl (2004) converge towards the same conclusions in their study of the differentiated renewal capabilities of clusters in a sample of old industrial areas; while Cho and Hassink (2009) find evidences according to which some clusters reach their maturity through an increasing rigidity of their networks that plays against their ability to react to market cycles.

Then clusters life cycles (Suire and Vicente 2009, 2013; Menzel and Fornahl 2010; Crespo 2011; Boschma and Fornahl 2012) can find explanations in the structural organisation of collaboration networks and their evolving patterns along the cycle of technologies and markets. Do successful clusters in a mature industry necessarily locked into a rigid trajectory and then to decline, or are there particular structural properties of localized collaboration networks that enable clusters to combine performance in mature industries and renewal capabilities towards emerging ones?

In order to disentangle this question, we propose in a second section to discuss the micro-motives of organisations for joining a network and building knowledge relations, and the resulting consequences on the emerging structural properties of knowledge networks. This section will show that network hierarchy and assortativity appear as two salient topological and structural properties that play together in the long term performance of localized R&D collaboration networks. Section three proposes to associate these structural properties to two statistical signatures of collaboration networks that provide tools for developing new evidences on the critical factors of the long term dynamics of clusters.

7.2 Clusters as R&D Collaboration Networks

7.2.1 Clusters Growth and Structuring

A cluster can now be defined as a local relational structure that results from the identification of a set of nodes of various institutional forms (the organisational demography) and the ties between them (the relational structure). Inter-organisational ties in a cluster can be of different nature (productive, commercial, cognitive or social) and of different geographical length. Our discussion focuses on localized R&D collaboration networks, and then organisational relations locally constructed to exchange knowledge in high-tech technological domains.

Network theory is very useful for analysing cluster properties, since it has identified several drivers of network formation (Ahuja et al. 2012) that can be founded on micro-economic behaviours. In particular, these micro-foundations are necessary to understand how new entrants join a cluster, and (re)shape its relational structure.

Firstly, networks can evolve through the entry of new nodes that do not connect to any other node (isolates), or through the entry of new nodes that connect to others by purely random attachment mechanism. It means that entering nodes connect to others with no particular preference for their position in the structure. Isolate entrants and random attachment mechanism will give rise to a rather flat hierarchy of degrees in the collaboration network. In terms individual strategies, both kinds of processes can be associated with a locational cascade (Suire and Vicente 2009). In locational cascades, new entrants draw pay-offs from belonging to the structure as a whole, not from targeted connections to particular nodes in the structure. Locational cascades have been largely evidenced for clusters that attract new organisations because of an external audience and a geographical charisma (Romanelli and Khessina 2005; Appold 2005). Organisations converge to a “locational norm” since the charisma displayed by one place in terms of R&D productivity provides a signal of quality and a strong incentive for being located there, whatever the position in the relational structure.

Secondly, entries can occur through a process of preferential attachment. In this opposite case, nodes with many ties at a given moment of time have a higher probability to receive new ties from new entering nodes. The higher the degree of an organisation in the collaboration network, the more this organisation is attractive for receiving new ties, so that the network grows through an increasing hierarchy (Albert and Barabási 2002). This behavioural pattern of nodes can be associated to a network effect in location decision externalities. This means that the more new entrants are connected to highly connected nodes, the more their payoffs increase, due to the benefits of reciprocal knowledge accessibility and technological connections to an emerging and growing standard. This branching process is now linked to targeted connections in the structure rather than random ones, and is consistent with the relational constraints that typify the production and diffusion of technological standards in high-tech industries and markets (Farell and Saloner 1985; Arthur

1989). It is also consistent with the relational behaviour of spinoffs that tend to connect to their often highly connected parent's company (Klepper 2010).

Beyond node entry, clusters structure themselves through the construction and dissolution of ties. The literature acknowledges two categories of individual incentives that shape social structures, and dissociate closure from bridging network strategies (Baum et al. 2012). Triadic closure implies that a node with links to two other nodes increases the probability for these two nodes to have a tie between them. Such an argument is grounded on the process of trust construction that grows between two related nodes, because it fosters cooperation and knowledge integration within groups of nodes. Closure in collaboration networks strengthens the mutual monitoring capability of organisations. Indeed, on one hand, it decreases the possibilities of opportunistic behaviours (Coleman 1988). On the other hand, it increases the effects of conformity required by technological standardization processes: without such closure, organisations can be tempted to play the battle of standards and accept the risk of a payoff decrease. As this process develops, the clustering coefficient of the network increases, and triadic closure tends to shape a core-component in the collaboration network (Borgatti and Everett 1999), in particular when closure prevails for highly connected organisations. The second category of individual incentives relates to bridging strategies and introduces the idea of a more disruptive relational behaviour. For a given network, bridging ties will be shaped when one organisation finds an opportunity to connect disconnected organisations or groups of organisations. Such an agency behaviour (Burt 2005) is more entrepreneurial than the former, since bridging provides access to new and non-redundant knowledge and new opportunities for improving innovation capabilities (Ahuja et al. 2009).

7.2.2 Structural Properties of R&D Collaboration Networks

According to the mechanisms of network formation and structuring at work in clusters, they will display a high degree of variability in the structural and topological properties of their collaboration network. Previously captured using different methodological approaches (Markusen 1996; Iammarino and McCaan 2006), this variety of cluster relational structures can be assessed using network theory through a set of simple key-indexes that echo important features of collaborative process of innovation.

The first property relies on the degree of connectedness of the collaborative network. A cluster will be fully connected if there is no isolates in the population of nodes and all the nodes can be reached by the other nodes. The second one is the density of the collaborative network. Clusters can have a very weak level of relational density if organisations value isolated strategies over knowledge partnerships. In that case, the clusters are no more than the simple result of a co-location process, as for the well-known satellite platform of Markusen (1993). On the contrary, clusters can display a high level of density when knowledge complementarities, trust and social proximity (Boschma 2005) lead to high levels of local cohesiveness into the collaboration network.

More importantly, even for a full connectedness and a fixed level of density, other structural properties matter and provides relevant information on the collaboration process. Considering the degree centrality of each organisation, i.e. direct interaction neighbourhood, the distribution of degree can vary from a flat distribution to an asymmetric one. To put it differently, the shape of the degree distribution refers to the hierarchy of positions in the web of relationships, and can be captured by ranking organisations in a network according to their degree and putting into relation with their own actual degree. Some organisations can have many relations due to a high relational capacity (König et al. 2010). This is generally linked to the size of the organisations, their absorptive capacities or the openness of their model of knowledge valuation. On the contrary, some others remain poorly connected due to their newness, their small size or their closed model of knowledge valuation.

Moreover, considering again the degree of each organisation, clusters can vary in their structure according the shape of the degree correlation. Indeed, clusters can display various levels of structural homophily, which is generally captured by an index of assortativity (Newman 2003; Watts 2004; Rivera et al. 2010). Here again, the assortativity of a network can be captured by the relation between the degree of each organisation and the mean degree of the organisations in its direct neighbourhood. The structure of relationships will be assortative when highly (poorly) connected nodes tend to be connected disproportionately to other high (weak) degree nodes. In that case, the degree correlation of the network is positive. At the opposite, the structure of relationships will be disassortative when highly (poorly) connected nodes tend to be connected disproportionately to other weak (high) degree nodes. In that case, the degree correlation of the network will be negative. Therefore, the level of network assortativity gives a formal representation of the way knowledge flows between central and more peripheral nodes.

How these properties can play together for that localized R&D collaboration networks perform of global markets without compromising their ability to adapt to business and market cycles? Recall that some successful clusters can decline when the market for their products decline, while some others succeed in disconnecting their cycle from the cycle of markets and develop renewal capabilities towards emerging ones.

The properties of hierarchy and assortativity provide new insights for that purpose. As a matter of fact, successful clusters at a moment in time and in a particular technological field are the ones that have succeeded in going from the exploration of new ideas to the exploitation of a technological standard or dominant design on a mass market, with in between, a collective process of knowledge integration between complementary organisations along the knowledge value chain (Cooke 2005). Beyond the traditional scheme of exploration/exploitation that typifies the innovation process of a single organisation, the knowledge integration phase is at the heart of the cluster's purpose. Indeed, the success of many products results from their degree of compositeness (Antonelli 2006), the variety of uses and applications supported by the products, scientific as well as symbolic knowledge (Asheim et al. 2011), and the compatibility and easy interoperability between elements that are the rule of a dominant design diffusion (Frenken 2006). The chasm that sometimes prevents some products from reaching the mass market (Moore 1991) is more often the consequence of a failed integration process, i.e. a problem of industrial organisation, rather than a problem of the product quality in itself. Successful clusters are therefore the ones that achieve the imposition of well-integrated and performing complete technological systems on mass markets. As the literature shows (Klepper and Simmons 1997; Audretsch et al. 2008), these clusters evolve from an initial scattered structure of burgeoning organisations in the early market stages to a structure with a limited number of hub and oligopolistic organisations in mature markets. Along the life cycle of products, and especially composite ones, such a network dynamic produces path dependence and technological lock-in. The more the technologies generate increasing returns to adoption, the more markets for these technologies become locked-in and resist to other competing technologies (Arthur 1989).

But are clusters producing these technologies necessarily locked-in too? The answer depends on the way in which their relational structure evolves along the life cycle of products. First, recall that R&D collaboration networks can grow through preferential attachment. This means that the more nodes display a high degree, the more newcomers connect to these nodes, engendering a high level of hierarchy in the degree distribution of organisations. But secondly, recall that beyond network growth through node entry, networks can also evolve by the addition and rewiring of ties between existing nodes through closure or bridging (Baum et al. 2012). When closure prevails, the cluster evolves towards a high level of transitivity between nodes which is the mark of isomorphic and conformist relational behaviours. In that case, the structure of the cluster exhibits tight couplings into a core-component and a loosely connected periphery of nodes. The ossification of the cluster goes with the formation of an assortative collaboration network, in which highly connected nodes are tied predominantly with other highly connected nodes, and poorly connected nodes remains connected between themselves. On the contrary, a structure with a disassortative web of knowledge relationships can emerge as the entry of newcomers and rewiring process go. For that, the node bridging strategy has to prevail over the closure strategy. Consequently, highly connected organisations spend a share of their relational capacity towards peripheral organisations, and the network as a whole displays more paths between highly and poorly connected nodes than for the assortative network.

The patterns governing the entry dynamics into networks and the structuring process that follows are at the heart of the lock-in/lock-out debate. Academics acknowledge that preferential attachment is a natural pattern of social and human networks that contributes to fostering the legitimacy of social norms and conformist effects in Sociology (Watts 2004), or technological standards and dominant designs in Business Studies (Frenken 2006). But the debate between closure and bridging is more controversial, and it is also controversial for cluster studies (Eisingerich et al. 2010). Indeed, closure favours technological lock-in and thus the ability of the relational structure to perform in markets. The tight coupling between high degree organisations favours conformism and trust in a stable and cohesive structure that prevents opportunism and promotes an efficient integration of knowledge in a context of weak environmental uncertainty. But closure favours network assortativity, and then prevents regional lock-out, since the low connectivity between the core nodes and the peripheral ones limits the re-organisation of knowledge flows when uncertainty grows or when the market starts to decline. So when preferential attachment and closure interact, the ability of clusters to deal with a positive technological lock-in goes against the collaboration network to produce the conditions for a regional lock-out (Simmie and Martin 2010).

In order to foster adaptability, clusters also have to develop bridging strategies in order to open more disruptive relations, preserving minimal cohesiveness in the core, while multiplying the channels for potential or latent flows of fresh and new ideas coming from peripherals nodes (Grabher and Stark 1997; Cattani and Ferriani 2008). Such a mix of patterns does not undermine the hierarchy of degrees that emerges when the technology goes towards exploitation. But to be disassortative, the oligopoly structure of hub-organisations that appears as the technology reaches maturity has to maintain a not too low amount of entrepreneurial connections with the periphery, in order to overlap exploitation in a particular knowledge domain and exploration in another related one (Cohen and Klepper 1992; Almeida and Kogut 1997; Schilling and Phelps 2007). Such a structural property of clusters is consistent with the behaviour of firms according to their maturity and age. Indeed, Baum et al. (2012) develop evidence on the predisposition of organisations to deal with closure or bridging strategies according to their age. Supposing that the age of organisations is positively related to their hub position and high degree, then the renewal capabilities of local knowledge structures can be weakened by an insufficient level of connectivity with newcomers, as shown by Saxenian (1990) for the semiconductor collaboration network in the Silicon Valley. If it is supposed that the capacity constraints in the amount of ties an organisation can maintain is related to its size and age, as König et al. (2010) do, then the high capacities of hub and central organisations can be a strong source of renewal if they go against the natural tendency to reproduce existing and conformist ties. Ahuja et al. (2009) find empirical evidence on that by capturing the micro motives for more disassortative behaviours. They highlight a threshold and non-monotonic effect in the strategy of embeddedness and closure between central nodes. According to them, the growing benefits in terms of trust and knowledge acquisition can go with an increasing rigidity and conformity that produces disincentives for new collaborations. Likewise, in spite of risks of knowledge hold-up and contract incompleteness, they find that peripheral organisations succeed in connecting to central nodes, through a "creeping" strategy facilitated by the ability of mature organisations to find sometimes new and disruptive opportunities to connect to peripheral newcomers.

7.3 Two Simple Statistical Signatures of Collaboration Networks

The level of hierarchy of node degree and the level of assortativity therefore appear as two simple statistical signatures of the ability of clusters to perform but also to avoid negative lock-in through their endogenous renewal capabilities. The following definition of statistical signatures of localized R&D collaboration networks aims to discuss the parameters space that allows clusters overlapping exploitation of technologies on mature markets and exploration of new or related technologies for emerging markets.

7.3.1 *Degree Distribution and Correlation*

Hierarchy and assortativity can be measured through two simple statistical signatures. The first corresponds to the degree distribution of the network. By degree distribution, we mean the relation between the ranking of nodes in a network according to their degree and their actual degree.[1] The more sloped the distribution is, the more the network displays hierarchy in the degree of nodes. From weakly connected nodes to highly connected nodes, the degree distribution exemplifies the level of heterogeneity in the network in terms of actual relational capacity. The second property corresponds to the degree correlation. Here, degree correlation is defined as the relation between the degree of each node and the mean degree of nodes in its neighbourhood. Networks can be characterized as assortative or disassortative to the extent that they display a positive or negative degree correlation. A network is assortative when high degree nodes are connected to other high degree nodes, and low degree nodes are preferentially connected to low degree nodes, so that the degree correlation is positive. And a network is disassortative when high degree nodes tend to connect to low degree nodes, and vice versa, so that the degree correlation is negative. For a given amount of nodes and ties in a particular network, one can easily capture these two salient properties.

Consider a fixed number of nodes and ties in a network N.[2] If we note k the degree of a particular node h, we can then write two simple equations to characterize the network topology. By referring to a rank-size rule, we can classify node degrees from the largest to the smallest[3] and then draw the distribution on a *log-log* scale. Such that:

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[1] Another traditional representation consists in mapping degree distribution using frequencies of degree values.

[2] Then we only focus on the structuring of the network. Entries are considered as exogenous, or occurring in previous periods.

[3] If two nodes have the same degree, we arbitrarily rank them as long as it has no incidence on the slope on the power law.

$$k_h = C\left(k_h^*\right)^a,$$

with k_h^* being the rank of the node h in the degree distribution, C a constant and $a < 0$ the slope of the distribution or equivalently,

$$\log(k_h) = \log(C) + a\log\left(k_h^*\right)$$

Secondly, we can calculate for each node h, the mean degree of the relevant neighbourhood (V_h), i.e.,

$$\overline{k_h} = \frac{1}{k_h}\sum\nolimits_{i \in V_h} k_i,$$

where k_i is the degree of node i belonging to the interaction neighbourhood of node h.

Then we estimate a linear relationship between $\overline{k_h}$ and k_h, such that

$$\overline{k_h} = D + bk_h,$$

with D a constant and b a coefficient capturing the degree correlation.

If $b > 0$, the network N exhibits assortativity with a positive degree correlation, whereas if $b < 0$, the network N is disassortative with a negative degree correlation.

Finally, thanks to the ordinary least squares method, the joint estimation of parameters a and b enables us to characterize useful structural network properties.

$$\begin{cases} \textit{degree distribution} : \log(k_h) = \log(C) + a\log\left(k_h^*\right) \\ \textit{degree correlation} : \overline{k_h} = D + bk_h \end{cases} \tag{7.1}$$

7.3.2 Discussion

Using Eq. 7.1, and considering a fully connected network N with a fixed number of nodes ($n = 33$) and ties ($t = 64$),[4] Fig. 7.1 summarizes this proposition, giving more details on three typical topologies and their statistical signatures.

(i) The so-called "flat" network presents a relatively flat degree distribution $|a| = 0{,}37$ with a degree correlation b ~ 0. This type of collaboration network displays a strong potential for knowledge flows re-organisation and diffusion since the nodes are linked by many paths. But such a random network does not succeed in generating conformity effects and the emergence of technological standards. Indeed, the lack of cohesiveness in to the network and the absence

[4] In such a way that the density remains the same for the three networks $2t/n(n-1) = 0.1212$, where t is the number of actual links and n the number of nodes).

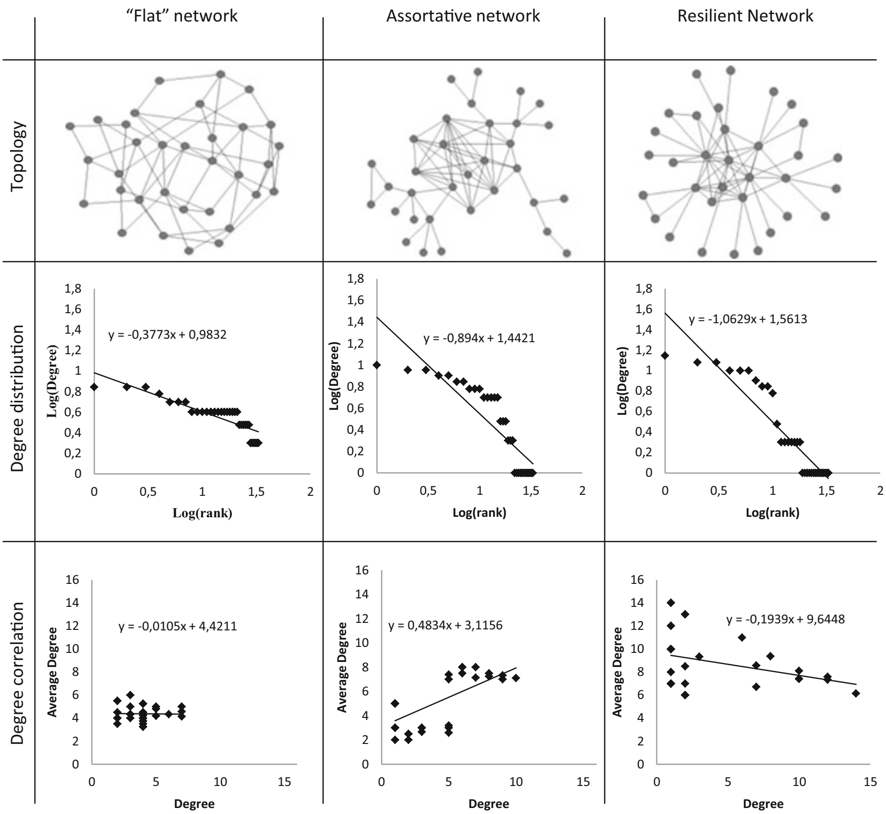

Fig. 7.1 Network topology, degree distribution and degree correlation

of a core group weaken the control of collective behaviours that would exploit products on the market by efficiently gathering pieces of knowledge.

(ii) On the contrary, the assortative network presents a strong slope in the degree distribution |a| = 0,89 so that the cohesiveness of the core promotes a conformity effect, and, from a technological perspective, a high probability of the emergence of a standard. Nevertheless, its strong assortative structure (b > 0) weakens its renewal properties since peripheral nodes are loosely connected to the central ones. This excess of assortativity will reduce the ability of the existing structure to activate new explorative ties when markets for the exploited technology decline, due to a weak level of bridging between the oligopoly structure and the peripheral ones. Therefore the assortative knowledge network favours technological lock-in without maintaining regional lock-out conditions because of its relative inability to overlap exploitation links on mature markets and explorative ones on emerging related ones.

(iii) Finally, the resilient network exhibits here again a high sloped degree distribution with |a| = 1,06, but the degree correlation is now negative (b < 0), so

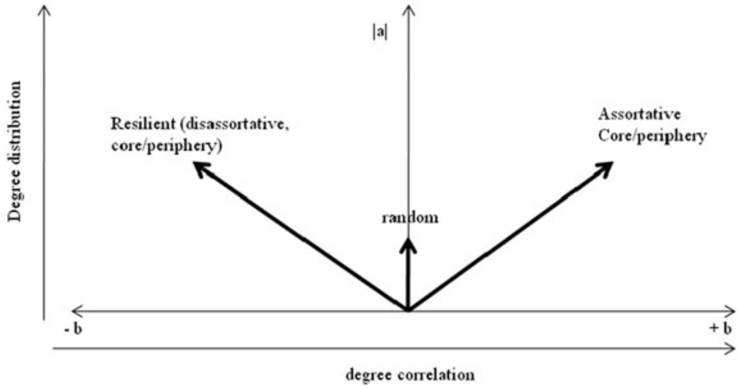

Fig. 7.2 Statistical signatures of cluster structural properties

that the network presents a certain level of disassortativity. In other words, this negative correlation indicates a high level of connections between the core and the periphery of the collaboration network, so that information and knowledge can circulate through many structural bridges between highly and poorly connected nodes. Thus targeted shocks on core members do not weaken the whole structure to the same extent as in the previous structure. Similarly, innovative or explorative behaviour can diffuse more easily from peripheral to central members, due to the ability of the oligopolistic organisations to combine closure and bridging and overlap explorative and exploitive phases in their relational patterns.

Figure 7.2 provides a more abstracted representation of these critical structural properties of local knowledge networks.

By representing degree distribution and degree correlation in the same layout, one can have a better understanding of how the structure and properties of local clusters can together improve aggregate performance and structural conditions for renewal along the cycles of markets. The further up in the layout a cluster is, the more the structural hierarchy of its collaboration network enables it to impose standards and dominant designs on markets. And the further left in the layout it is, the more the disassortative patterns of relationships in the network increase regional renewal capabilities. The emerging oligopolistic structure that arises when the technology reaches maturity has to remain sufficiently linked to fresh and new ideas coming from peripheral but promising nodes for future collaborations. On the other hand, when closure strategies in the mature oligopolistic structure exceed a certain threshold, then redundancy of knowledge flows and conformity effects prevail and the possibilities for regional resilience fall unavoidably. Then if some clusters decline when their dedicated markets decline, the reasons are not necessarily to find in an ossification of the structure of the network or in an excess of rigidity due to the firm growing size, but in the relational strategies of hub and leading organisations, and a decreasing degree of openness towards peripheral but strategic newcomers.

7.4 Conclusion

In spite of its high level of abstraction and complexity, the science of networks applied to geography of innovation provides promising perspectives for static as well as dynamic analysis of clusters. Here we have tried to show that it was possible to reduce this complexity to two simple statistical signatures of collaboration networks. Degree distribution and degree correlation highlight the critical structural properties that increase the performance of clusters in a particular technological field, without decreasing their renewal properties. If the hierarchy of degrees is a more or less common pattern of social and organisational networks, disassortativity is less manifest. Indeed, human and social behaviours are generally characterized by structural homophily, so that the more an agent increases its relational capacity, the larger is his tendency to interact with other highly connected agents. However, this property of assortativity of local knowledge networks weakens the ability of clusters to combine market exploitation and absorption of fresh and new ideas, and then, can be a source of negative regional lock-ins.

The combined measures of degree distribution and degree correlation confirm that a window of parameters exists, for which clusters can display performance in the short run, and renewal capabilities in the long run. Capturing this window more precisely requires an additional effort of modelling. But at this stage, such a framework furnishes new perspectives to highlight empirical evidence on the ability of regional systems of innovation to resist and adapt to turbulent macroeconomic environments, new growing consumer paradigms and the shortening of market cycles.

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